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Citation for published version:

Sheehy, S, Edwards, G, Dent, C, Kazemtabrizi, B, Troffaes, M & Tindemans, S 2016, Impact of high wind penetration on variability of unserved energy in power system adequacy: International Conference on Probabilistic Methods Applied to Power Systems (PMAPS). in *2016 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*. Institute of Electrical and Electronics Engineers (IEEE), Beijing. <https://doi.org/10.1109/pmaps.2016.7764199>

Digital Object Identifier (DOI):

[10.1109/pmaps.2016.7764199](https://doi.org/10.1109/pmaps.2016.7764199)

Link:

[Link to publication record in Edinburgh Research Explorer](#)

Document Version:

Peer reviewed version

Published In:

2016 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)

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Impact of High Wind Penetration on Variability of Unserved Energy in Power System Adequacy

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Abstract—This paper presents results on variability of out-turn shortfalls about the expected value indices which are usually presented in resource adequacy studies, for a range of Loss of Load Expectation (LOLE) levels and installed wind capacities in a test system generally representative of future Great Britain system scenarios. While the details of results will clearly vary between systems, one very general conclusion is possible. In the results presented, for a given LOLE level, the probability of very severe out-turn in a future peak season is much greater at high installed wind capacity. Thus for this system, as the installed wind capacity increases, a constant level of LOLE cannot be taken as an indicator of an unchanging overall risk profile of the system. This further demonstrates that in *any* system, LOLE cannot be assumed to be a good summary statistic of risk profile as the installed variable generation (VG) capacity increases, and that it might be necessary to reconsider the near-universal use of expected value risk indices as the main headline indices in utility adequacy studies.

I. INTRODUCTION

Security of supply in power systems with high wind penetration has been of great interest in the industry and in the research literature. In contrast to conventional generation, wind generation features far more variability and uncertainty both on operational and planning timescales, as well as strong spatial correlations. In this paper, we will solely focus on system adequacy on a planning timescale i.e. the long term time evolution of security of supply. Consequently, following standard practice in many resource adequacy studies, we will not be concerned with reserve setting, stability in system operation, or network capacity constraints.

In practical adequacy studies at whole-system level, and in the research literature, the headline risk model outputs presented are usually the expected value of some measure of out-turn – most commonly LOLE (the expected duration of shortfall, or number of periods of shortfall, in the future season under study), but also sometimes Expected Energy Unserved (EEU), also referred to by various alternative names including Expected Energy Not Supplied (EENS) [1], [2], [3], [4]. Indeed the principal change in reporting of model outputs in recent years has been a move from most studies reporting LOLE on a resolution of daily demand peaks, to some reporting LOLE on a time resolution of hours or half hours (hourly LOLE sometimes being referred to as LOLH). For

relatively simple systems, the required risk measures (LOLE, EEU, etc.) can be computed efficiently by convolution or state space sampling with a non-sequential or time-collapsed model [3], [2], [5].

A criticism against expected value indices such as LOLE is that they only provide a point estimate, and do not contain information on variability of out-turn about the mean. Expected value indices such as LOLE might reasonably be thought to summarise how the overall risk level changes from year to year in a system whose overall profile of demand and installed supply stays broadly the same. However, in a system where the installed capacity of wind (and other variable technologies) is increasing rapidly, such risk indices may no longer provide a useful summary statistic – as the variability of supply increases, the variability of out-turn is naturally expected to increase as well, rendering classic expected value indices unsatisfactory as summaries of the overall risk profile.

To quantify also the variability of unserved energy, a sequential model is required [6], which usually can only be evaluated through Monte Carlo simulation. Studies discussing variability of annual out-turn using sequential models include at distribution level [7], [8] and at transmission level [9]. The resulting risk profiles can be presented directly to planners, or processed to extract features of interest [10]. Due to their flexibility, sequential models with outputs evaluated by Monte Carlo simulation form the basis of major commercial adequacy assessment tools, e.g. MARS [6], [11] and ANTARES [12].

The increasing penetration of variable renewable generation requires development of realistic approaches to incorporate these resources into adequacy studies. A substantial effort has been made to develop time series models for available wind capacity [13], [14]. However, to the best of our knowledge, little attention has been given to the impact of the wind penetration level on the variability of unserved energy.

This paper will explore the variability of unserved energy, in a standard adequacy model using data based on the Great Britain (GB) system. We will demonstrate that wind penetration has a substantial impact on this variability. Thereby we argue that expected value indices, such as LOLE, are inadequate to provide a full picture of the risk. Section II describes the model and model outputs and Section III describes the

data used for the example presented in Section IV. Section V concludes the paper.

II. MODEL DESCRIPTION

A. Model

The quantity of primary interest is the following discrete time stochastic process describing the system margin:

$$Z_t := X_t + Y_t - D_t \quad (1)$$

where X_t is conventional capacity, Y_t is wind generation, and D_t is demand. The time step Δ is one hour, reflecting the resolution of data, described in Section III.

Each conventional unit is modelled as a two-state Markov process, i.e. the available capacity from each unit is either maximal or zero. Units are assumed independent, and the total available capacity X_t is the sum of the capacity from the individual units. Section III-B has more detail.

Wind, Y_t , is modelled using a logit transformed autoregressive (AR) process, with an extra term to capture variability in the yearly mean, as described in Section III-D.

Statistical modelling of demand D_t is a considerable challenge. Therefore in this study, also following [14], we condition all results on a historic demand trace taken from a specific year in the data as described in Section III-C.

B. Model Outputs

The duration of shortfall DS, in hours per year, and energy unserved EU, in MWh per year, are defined as

$$DS := \sum_t I_{Z_t < 0} \quad (2)$$

$$EU := \sum_t \max\{-Z_t, 0\} \quad (3)$$

Here, $I_{Z_t < 0}$ is 1 if $Z_t < 0$ and 0 otherwise, and for simplicity as the data are on an hourly resolution we do not write explicitly the time step Δ . The expectations of these random quantities are the LOLE (loss of load expectation) and the EEU (expected energy unserved):

$$LOLE := E(DS) = \sum_t P(Z_t < 0) \quad (4)$$

$$EEU := E(EU) = \sum_t E(\max\{-Z_t, 0\}) \quad (5)$$

Such expected value indices are typically used as the headline indices in practical adequacy assessment studies, however they do not contain information on variability of duration of shortfalls or energy unserved. More detailed model outputs are required in order to study for instance how this variability increases when VG increases.

This paper will report the following model outputs:

- The distribution of the duration of shortfall (DS);
- The distribution of energy unserved (EU), evaluated both in MWh per year and as a proportion of total demand;
- The distribution of the number of days on which there is a shortfall.

TABLE I
GENERATOR AVAILABILITIES AND REPAIR TIMES BY FUEL TYPE

Fuel Type	Availability Probability	MTTR (hours)
Coal/Biomass	0.88	40
Gas CCGT/CHP	0.85	50
Gas OCGT	0.92	50
Oil	0.82	50
Nuclear	0.81	150
Hydro	0.84	20
Pumped Storage	0.96	20

III. DATA

A. Adjusted Gone Green Scenario

The results in this paper are based National Grid's 2013 Gone Green (GG) Scenario for winter 2013/14, a summary of which can be found in [15]. The generating unit capacities are slightly adjusted from the original GG scenario – this will be referred to as the Adjusted Gone Green (AGG) scenario. The data are modified due to the politically sensitive nature of adequacy assessment results using the original National Grid scenarios, however the results presented remain generally representative of adequacy assessment results for the GB system. This section will describe in detail the data used to fit the conventional plant, demand and wind models.

B. Conventional Generators

The AGG scenario contains 272 conventional generation units, with total capacity 68,450 MW. The availability probabilities for each class of technology are taken from the AGG scenario. Mean Time To Repair (MTTR) values are taken from similar units in the 1996 IEEE Reliability Test System [16]. These values uniquely determine the transition rates for each Markov chain. Table I shows the MTTRs and availability probabilities by fuel type.

An improvement over [14] is that in this study, we directly simulated times to failure and times to repair, which is much more efficient than simulating transitions at each time step.

C. Demand

Demand is assumed to be a fixed deterministic time series from a specific historic winter, rescaled according to underlying peak demand level as represented by the 'Average Cold Spell' (ACS) peak statistic. The ACS peak is the median out-turn peak demand level in a winter, conditional on the prevailing underlying demand patterns, the variability in out-turn peak being due primarily to weather – it provides a means of comparing how high out-turn demands are between different historic winters, and rescaling historic demand traces to a common underlying demand level for forward looking risk calculations.

Historic demand time series are available for 7 winters from 2005-11, each being 20 weeks in length starting on the first Sunday in November. These are based on transmission-metered demand values, available from [17], with an estimate of embedded generation added back on so that in forward looking calculations transmission- and distribution-connected

wind are treated on a common basis. All results in this paper are based on the demand trace from 2010/11, as this is as this is the winter with the highest demand relative to the underlying ACS peak demand level for that season. For the 2013/14 AGG scenario used in this paper, the ACS peak is 55.55GW.

As in [5], 700 MW is added to all demand values to account for the response (primary reserve) required by the system operation to cover sudden losses of in-feed. The system operator will take emergency actions such as voltage reduction or disconnections in preference to eroding this response requirement. For the purposes of this paper, a shortfall is defined as failing to meet 100% of demand plus the response requirement.

D. Wind

Following [14], we directly model the aggregated power output of the transmission-connected wind fleet in the 2013/14 AGG scenario, (total capacity 10,120 GW), and use a time series model to simulate winter-long traces. The time series model was fitted to historical wind data associated with the scenario, as described in [14]. The model comprises of an AR(5) process including a random seasonal mean, followed by a logistic transform.

The full model equations for the aggregated wind power during hour t of year v are:

$$\text{logit}(Y(v, t)) = Y_1(v) + Y_2(v, t) \quad (6)$$

$$Y_1(v) \sim N(\mu, \sigma_1^2) \quad (7)$$

$$Y_2(v, \cdot) | v \sim \text{AR}(\alpha_1(v), \dots, \alpha_5(v), \sigma_2(v)) \quad (8)$$

where $Y_1(v)$ captures the yearly variable mean, and $Y_2(v, t)$ is an AR(5) process. As wind power is a bounded process it cannot be modelled via a standard AR process without further non-linear transformation. The logit transform achieves normality of the residuals, and is defined as $\text{logit}(y) := \log(t(y)/(1-t(y)))$ where $t(y) = (y-a)/(b-a)$. As in [14], $a = 120$ and $b = 8900$ were chosen to achieve normality as closely as possible.

The original wind time series associated with the AGG scenario correspond to historical wind patterns for the winters 2005-2011. Historical wind speeds at the wind farm locations in the 2013 scenario were converted to wind powers using a single power curve, then scaled to reflect the capacity at each location, and aggregated. Although it would be possible to do a sensitivity analysis across AR coefficients fitted against different years, the impact of the wind model on model outputs is reasonably limited [14].

In this study, we chose the AR model coefficients that best fit the 2010/11 historical wind power series, i.e. $Y_2(v, \cdot) | v = 2010$. The resulting wind traces are rescaled to give traces representing different installed capacities: 1, 10, and 30GW. While it is unrealistic to assume that 1 GW of installed wind capacity has the same spatial distribution as 30GW, consistency in this regard is appropriate for the numerical experimentation within the present study, as it allows exploration of the variation of results with installed capacity while keeping the wind process load factor the same.

TABLE II
ADEQUACY INDICES FOR ALL LOLE 1 SCENARIOS

Index	0GW	1GW	10GW	30GW
Scaling	0.9641	0.9706	1.0057	1.0418
LOLE	1.004	0.992	1.000	1.004
EEU	845.0	836.1	953.3	1127
LOLDays	0.541	0.539	0.517	0.484

TABLE III
ADEQUACY INDICES FOR ALL LOLE 3 SCENARIOS

Index	0GW	1GW	10GW	30GW
Scaling	0.9836	0.9902	1.0284	1.0697
LOLE	2.995	3.017	2.986	3.025
EEU	2852	2855	3280	4039
LOLDays	1.525	1.540	1.439	1.336

E. Choice of Model Runs

Model outputs will be presented for 12 combinations of installed wind capacities and ACS peak demand levels, with each combination representing a new scenario – this allows exploration of the differences in risk profile with wind capacity and risk level. As stated above, we explore wind capacities of (0, 1, 10, 30) GW and, for each case, rescale the AGG demand trace so that the LOLE takes values of (1, 3, 10) hours/winter. The original set of conventional units in the AGG scenario is retained in each new scenario. The stopping criterion for each simulation is 10,000 observations of a year with a shortfall.

IV. RESULTS: DISTRIBUTION OF OUTCOME SEVERITY

The distributions of the various whole-peak season outcome measures are plotted in Figs. 1 to 3, for different levels of LOLE and installed wind capacity. Fig. 1 contains the distribution of duration of shortfall in the peak season under study (DS, of which LOLE is the mean), Fig. 2 contains the distribution of energy unserved (EU), of which EEU is the mean), and Fig. 3 contains the distribution of the number of days on which a shortfall occurs. The corresponding expected value indices are shown in Tables II to IV, where LOLDays is the expected number of days per year on which there is a shortfall.

Across all of these representations it is clearly seen that at all LOLE levels the variability of out-turn is much greater at higher installed wind capacity, with the increase in variability of out-turn as wind capacity increases being greatest at high LOLE. It is natural to expect that upscaling variable components of generation, such as wind, will lead to an increase in variability of outcome measures, an effect which is in the case

TABLE IV
ADEQUACY INDICES FOR ALL LOLE 10 SCENARIOS

Index	0GW	1GW	10GW	30GW
Scaling	1.0095	1.0162	1.0589	1.1086
LOLE	10.00	10.02	10.00	10.00
EEU	11406	11383	13367	16731
LOLDays	4.628	4.666	4.341	3.891

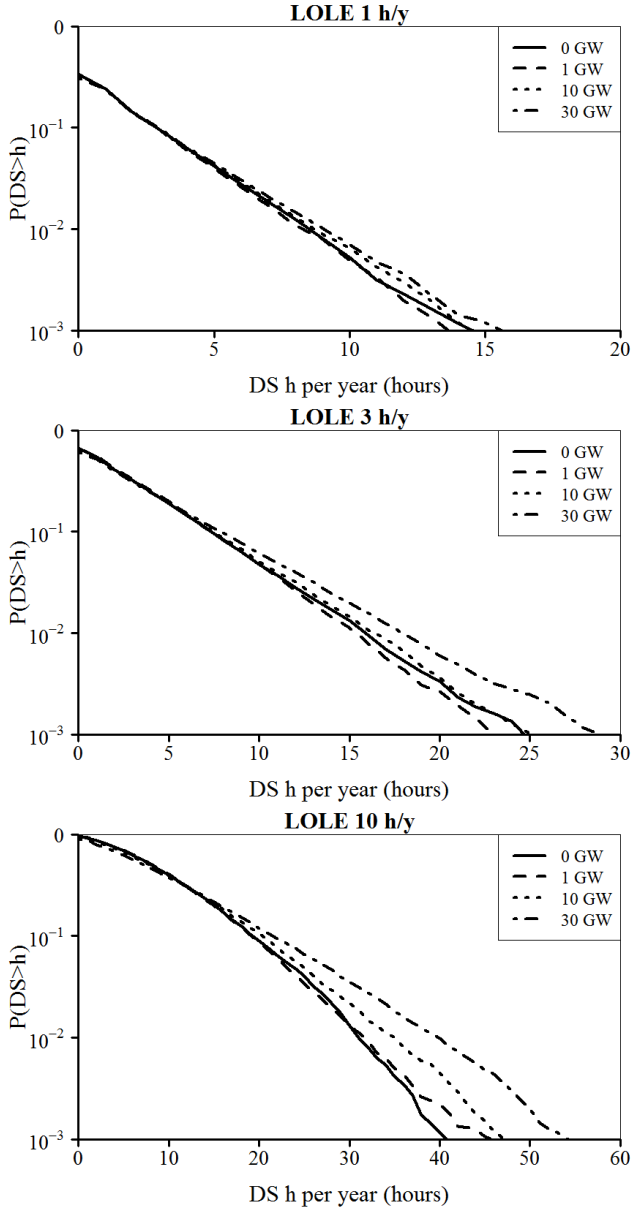


Fig. 1. Distribution of duration of shortfall (DS) for different LOLE levels and installed wind capacities.

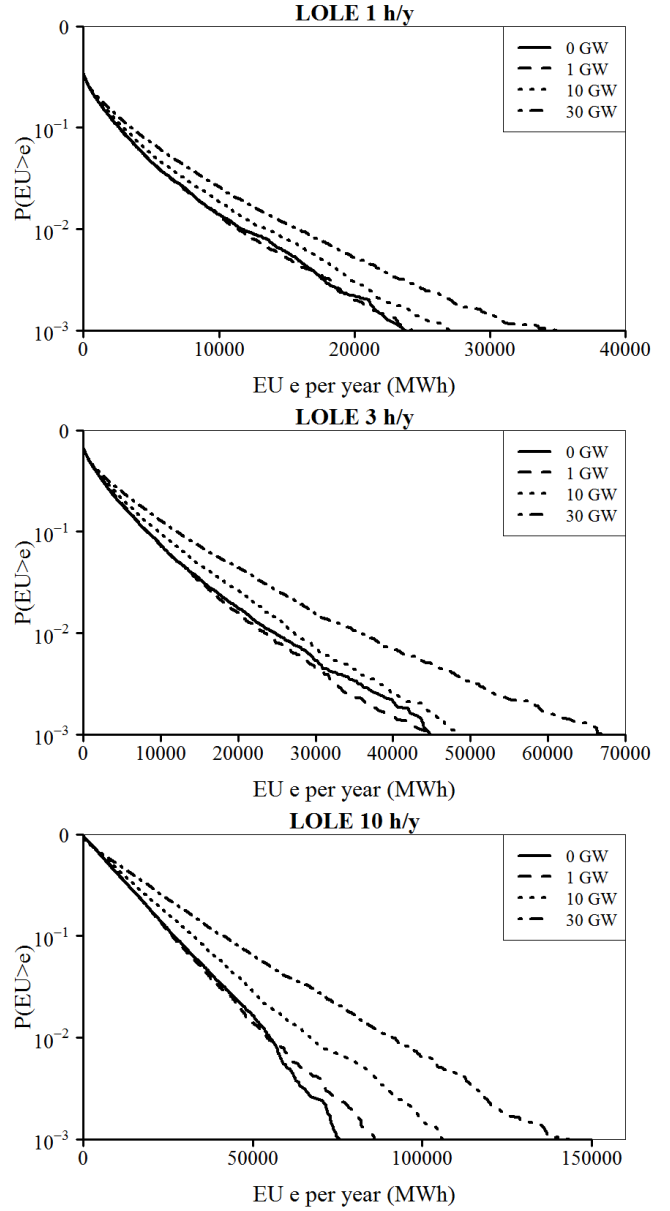


Fig. 2. Distribution of unserved energy (EU) for different LOLE levels and installed wind capacities.

of wind magnified by available wind capacity being correlated through time. These results demonstrate how substantial this effect can be in a realistic exemplar.

For comparison, Fig. 4 displays the same data as Fig. 2, except with EU normalised by total energy demand across the peak season. The broad trends remain the same, however the increase in variability of out-turn (as wind capacity increases) is slightly lower in the normalised representation. While this difference from the original MWh representation of EU is small, it is a matter for policy decision makers whether it is the absolute volume or percentage of energy unserved which should be regarded as the more significant metric.

V. CONCLUSION

This paper has presented results on variability of out-turn shortfalls about the expected value indices which are usually presented in resource adequacy studies, for a range of LOLE levels and installed wind capacities in a test system generally representative of future Great Britain system scenarios.

While the details of results will clearly vary between systems, one very general conclusion is possible. In the results presented, for a given LOLE level, the probability of very severe out-turn in a future peak season is much greater at high installed wind capacity. Thus for this system, as the installed wind capacity increases, a constant level of LOLE cannot be taken as an indicator of an unchanging overall risk profile

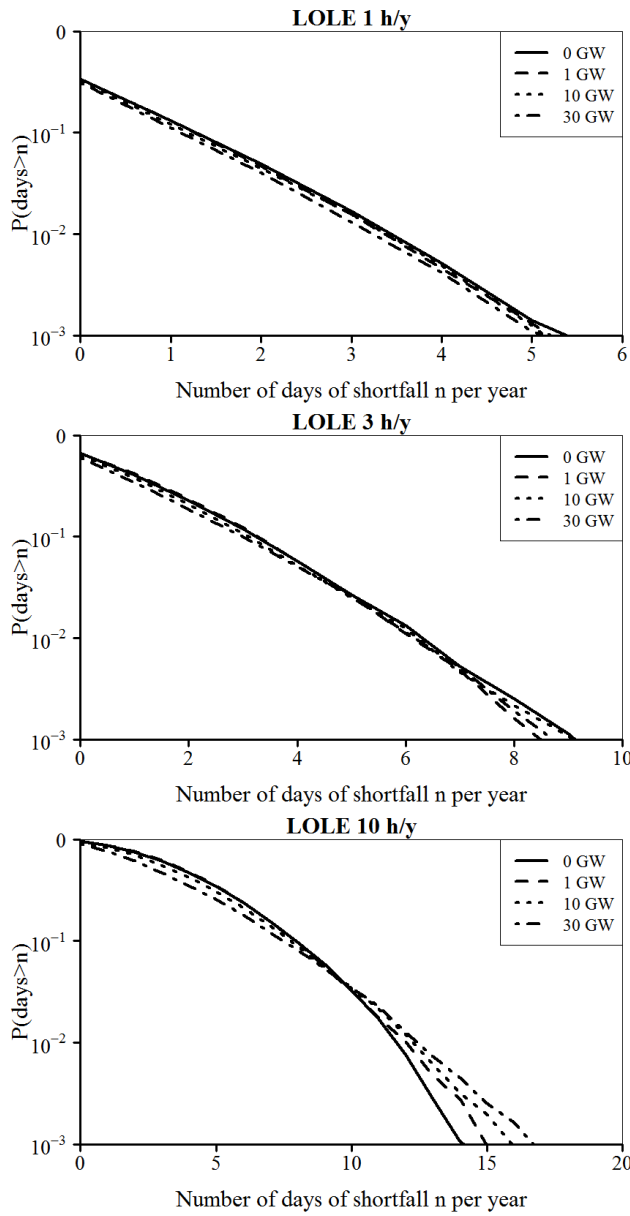


Fig. 3. Distribution of the number of days of shortfall per year.

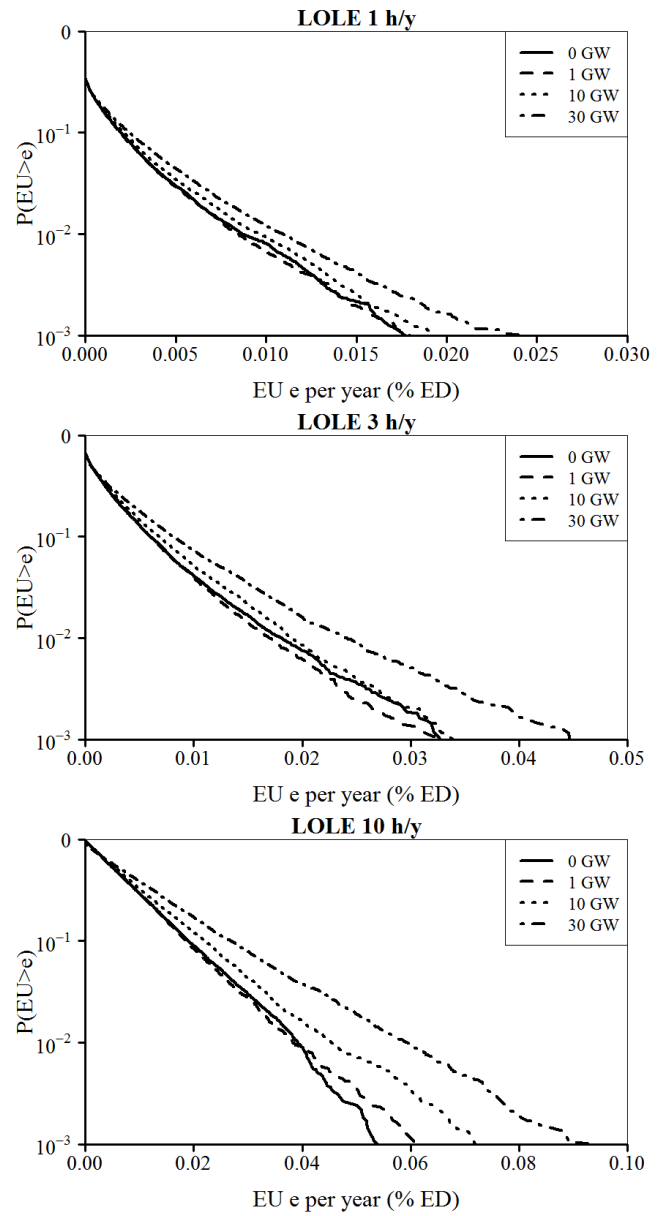


Fig. 4. Distribution of energy unserved (EU) as a proportion of total energy demanded (ED).

of the system. This further demonstrates that in *any* system, LOLE cannot be assumed to be a good summary statistic of risk profile as the installed VG capacity increases, and that it might be necessary to reconsider the near-universal use of expected value risk indices as the main headline indices in utility adequacy studies.

ACKNOWLEDGMENT

The authors would like to thank S. Zachary and A.L. Wilson, and colleagues at their own institutions, at National Grid and in the IEEE LOLEWG for valuable discussions. This work was supported by EPSRC grants EP/K036211/1 and EP/K002252/1, and by S. Sheehy's EPSRC PhD studentship. S. Tindemans's contribution relates to work funded by the UK

Energy Research Centre as part of the Future Energy System Pathways programme. UKERC is funded by the Research Councils Energy Programme.

REFERENCES

- [1] NERC BAL-502-RFC-02, establishing LOLE as standard for the ReliabilityFirst region. [Online]. Available: <http://www.nerc.com/files/BAL-502-RFC-02.pdf>
- [2] R. Billinton and R. N. Allan, *Reliability evaluation of power systems*, 2nd edition. Plenum, 1994.
- [3] A. Keane, M. Milligan, C. J. Dent, B. Hasche, C. D'Annunzio, K. Dargoon, H. Holttinen, N. Samaan, L. Soder, and M. O'Malley, "Capacity Value of Wind Power," *IEEE Transactions on Power Systems*, vol. 26, no. 2, pp. 564–572, May 2011.
- [4] (2015) National Grid EMR Electricity Capacity Report. [Online]. Available: <https://www.emrdeliverybody.com/Capacity/%20Markets/>

- [5] C. J. Dent and S. Zachary, "Further results on the probability theory of capacity value of additional generation," in *Probabilistic Methods Applied to Power Systems (PMAPS), 2014 International Conference on*. IEEE, 2014, pp. 1–6.
- [6] G. E. Haringa, G. A. Jordan, and L. L. Garver, "Application of Monte Carlo simulation to multi-area reliability evaluations," *IEEE Computer Applications in Power*, vol. 4, no. 1, pp. 21–25, Jan 1991.
- [7] L. Goel and R. Billinton, "Monte Carlo simulation applied to distribution feeder reliability evaluation," *Electric Power Systems Research*, vol. 29, no. 3, pp. 193–202, 1994. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/0378779694900140>
- [8] R. N. Allan and M. G. D. Silva, "Evaluation of reliability indices and outage costs in distribution systems," *IEEE Transactions on Power Systems*, vol. 10, no. 1, pp. 413–419, Feb 1995.
- [9] R. Billinton and A. Jonnavithula, "Application of sequential Monte Carlo simulation to evaluation of distributions of composite system indices," *IEEE Proceedings - Generation, Transmission and Distribution*, vol. 144, no. 2, pp. 87–90, Mar 1997.
- [10] S. H. Tindemans and G. Strbac, "Visualising risk in generating capacity adequacy studies using clustering and prototypes," in *Power Energy Society General Meeting, 2015 IEEE*, July 2015, pp. 1–5.
- [11] B. Bagen, P. Koegel, M. Couillard, K. Stradley, B. Giggee, A. Jensen, J. Iverson, and G. E. Haringa, "Probabilistic resource adequacy assessment of large interconnected systems," in *Probabilistic Methods Applied to Power Systems (PMAPS), 2010 IEEE 11th International Conference on*, June 2010, pp. 252–258.
- [12] M. Doquet, C. Fourment, and J. M. Roudergues, "Generation and transmission adequacy of large interconnected power systems: A contribution to the renewal of Monte-Carlo approaches," in *PowerTech, 2011 IEEE Trondheim*, June 2011, pp. 1–6.
- [13] R. Billinton, H. Chen, and R. Ghajar, "A sequential simulation technique for adequacy evaluation of generating systems including wind energy," *IEEE Transactions on Energy Conversion*, vol. 11, no. 4, pp. 728–734, Dec 1996.
- [14] M. C. M. Troffaes, E. Williams, and C. J. Dent, "Data analysis and robust modelling of the impact of renewable generation on long term security of supply and demand," in *Power & Energy Society General Meeting, 2015 IEEE*. IEEE, 2015, pp. 1–5.
- [15] (2013) National Grid Electricity Ten Year Statement. [Online]. Available: <http://www2.nationalgrid.com/UK/Industry-information/Future-of-Energy/Electricity-ten-year-statement/ETYS-Archive/>
- [16] P. Wong, P. Albrecht, R. Allan, R. Billinton, Q. Chen, C. Fong, S. Haddad, W. Li, R. Mukerji, D. Patton *et al.*, "The IEEE Reliability Test System-1996. A report prepared by the reliability test system task force of the application of probability methods subcommittee," *Power Systems, IEEE Transactions on*, vol. 14, no. 3, pp. 1010–1020, 1999.
- [17] National Grid: Demand Data. [Online]. Available: <http://www2.nationalgrid.com/uk/Industry-information/electricity-transmission-operational-data/>